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Digital Footprints – recording bot movement and behaviour to improve AI opponents in FPS games

Thomas Welsh[1)], David C. Moffat[1)] and Alastair Hebson[2)]

Abstract. To improve the experience for games players in FPS games, it is important that AI controlled bots are not only challenging and compelling opponents but also authentically human-like. This paper considers the use of an FPS visualization tool created by the authors called *Digital Footprints* to analyse and evaluate bot play behavior. This visualization tool gathers data and formats it as a series of heat maps which provide easy to understand diagrammatic representations of the events of a game session. By examining this data, the conclusion drawn is that current AI controlled bots exhibit key differences in their play behaviour to human players which reduces their believability and therefore diminishes the play experience for the player.

1 Introduction

Artificial intelligence in games is no longer a luxury; it is an aspect of game design which is integral to an engaging game experience[1]. With increasing visual fidelity available due to hardware advances in home consoles and PCs, more resources are available to developers and designers to create engaging behaviour for their artificial characters in their increasingly convincing virtual worlds [2]. If a game environment sets a level of expectation in the player which the virtual inhabitants of that environment cannot match then the artificial intelligence of the game will be the aspect which limits the experience and enjoyment of the player [3].

This paper concerns itself with the evaluation of the Artificial Intelligence applied in one genre of game, the first person perspective shooting game. First Person perspective Shooting games (FPSs) are amongst the most popular form of game on the PC[4]. In these games, the player does not see their on-screen avatar. The player simply sees the weapon they are carrying and a cross hair to represent where their weapon will shoot. They are able to walk forwards, walk backwards, turn, sidestep (strafe) and jump[1]. A number of different game rules can apply in an FPS game but generally the player's goal is to kill their opponent as many times as possible. Each kill, also known as a frag, adds to the players score. Typically, when a player is killed they will have to wait for a set period of time before being reborn (spawned).

FPSs can be online multiplayer games or narrative based games. Narrative based games often have a complex storyline which progresses as you play (e.g. Half Life 2) or in some cases very simple storylines (e.g. Doom). Narrative based games are usually one-player games where the computer controls the actions of all inhabitants of the game world other than the player. Online multiplayer FPSs can have computer-controlled inhabitants too, which can take the place of human players. These computer-controlled opponents are referred to as bots. At this point it is worth stating that the differentiation between online FPSs and narrative FPSs is much less well defined than in the past [5]. Games like Halo 3 and Call of Duty 4 have a comprehensive single player narrative campaign as well as a robust multiplayer online component [6].

In an online FPS game, a typical rule set is a deathmatch. The term deathmatch in this instance merely refers to a specific set of rules that govern a battle between groups of players in an FPS game. Any of these players may be controlled by bots or be human players. In a deathmatch, the player's battle until an arbitrary number of frags is reached or a time allocation expires. The player with the most frags wins. The deathmatch rule set therefore provides a simple game structure into which we can place bots to evaluate their performance [7].

This paper looks at the bots available in the popular FPS game *Unreal Tournament 3*. These bots are evaluated using the *Digital Footprints* visualization tool which has been developed by one of the authors of this paper. *Digital Footprints* gathers data and creates visualizations on the major events of an FPS game, focusing on the movements and the actions of the players. The rich data that *Digital Footprints* can generate will be used to evaluate the differences between human and bot play behavior.

The importance of this research is that it will determine if the current state of single player AI in FPS games is sufficient to create an engaging play experience. Should the bots in FPS games exhibit behavior markedly different to human players, then the significance of these differences on play experience must be considered.

The first goal of this research therefore is to measure the current success of AI in FPS games to determine if improvements need to be made. It is assumed that the computer controlled AI will provide a less compelling games playing experience than facing human players and game flow will suffer as a result [8].

2 Methodology

The visualisation tool, *Digital Footprints*, has a number of possible uses, but one of the most important is its ability to record player data for both bots and humans to aid in the understanding of both. The tool records information on the movements and actions of game characters whether they are player avatars or computer controlled bots and provides valuable data which can be used to evaluate and inform the programming of AI controlled Bots.

In a typical FPS game the player views the action from the first person perspective. In this view the player sees what his in game avatar sees and as a result has a limit on the amount of information available. The player would not be able to determine where his opponents were or what actions they were taking unless they were within his or her line of sight.

Digital Footprints shows a plan view of the level that the players inhabits and thus provides an overview of where all players are and what they are doing. This in itself is of use for any research into game play behaviour as it gives the researcher a greater breadth of information than a single point of view of any one player and is also

[1] Glasgow Caledonian University

[2] Rockstar North, 1 Greenside Row, Edinburgh

easier to follow than watching the action from the viewpoint of multiple players.

For the purposes of this research, *Digital Footprints* was used in the *Unreal Tournament 3* game engine using the *Rising Sun* level. This map takes place “outside” meaning that there is no ceiling above the players and the game takes place on a flat plane with no multi-level buildings. Although *Digital Footprints* can be used on maps with multiple levels, a simple map was chosen in this case to make the heatmaps easier to read. Figure 1 shows the map using the game graphics and figure 2 shows the wireframe model of the map.

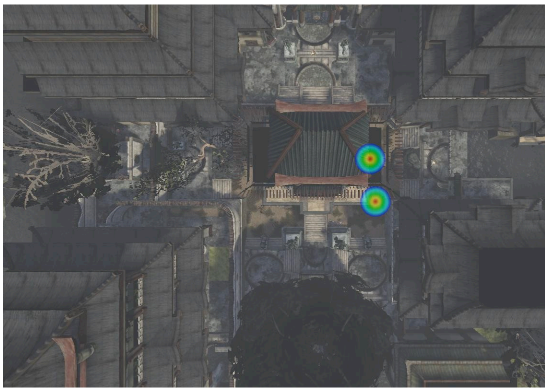

Figure 1. Map of *Rising Sun* level as rendered by game engine

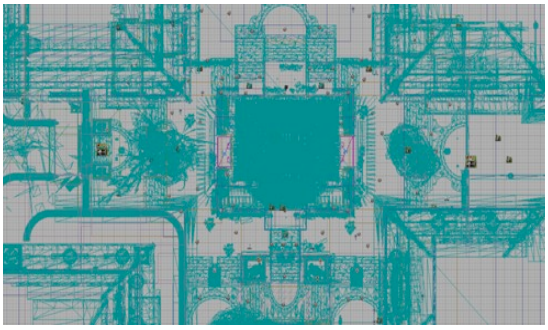

Figure 2. Map of *Rising Sun* level in wireframe

Beyond the relatively simple 2D overview provided by the application, the tool includes a number of additional functions intended to help analyse the data it gathers. It can highlight areas of a displayed map based on the amount of time spent in that area by the players. This heat map allows the user of the tool to determine the busiest parts of the map and the areas where either Bot or human players fail to explore. A simpler version of this type of heat map was used in the development of Halo 3 [9]. In that case, the heatmaps showed only human player navigation through a level and was used to balance the difficulty and play test the single player campaign. Currently Digital Footprints is only compatible with Unreal Tournament 3 but future versions could be adapted to work with multiple game titles.

If both human and Bot players avoid a particular part of the map then this may or may not be an acceptable outcome. If the level designer was to make use of this tool, they may decide that it is unacceptable to have parts of the map which are not explored often or at all. For the AI programmer however, it makes little difference if the bots and humans avoid the same areas and is broadly indicative of a success on the part of the Bot.

However, if it is found that the Bots and the human players frequent different areas of the map then the Bot is in most likely failing to exhibit believable human-like AI. At the most basic level the Bots navigation path around the level is different to the humans and this ranks as one of the most obvious giveaways. The human player will quickly be able to determine the bot nature of their opponents merely by observing their geographical placement in the game world.

This visual shading of the overview map provided by the visualisation tool can be seen as a useful resource when developing and testing Bot AI. If sections of the shaded map for the Bot are significantly different from the human player versions then changes in the path finding or high level AI can be done to alleviate one of the most obvious giveaways exhibited by Bots. This represents the most basic functionality offered by the visualisation tool.

The visualisation tool also monitors the weapon use of all players in the game. Number of shots fired, accuracy, ammo used and collected and a number of other statistics are available as log files or can be overlaid directly onto the visualised map. Again, the comparison of these statistics can be done easily. Analysis of this data will provide insight into the human and bots behaviour after the game is completed. Additionally the diagrammatic view will in some cases provide direct and obvious differences in the behaviour of the Bots and humans. One example would be the number of shots fired. By examining the heat map, it will be very clear if the human controlled players are firing their weapons more often than the Bots or vice versa. This is another area of bot behavior which can be easily modified.

The visualisation tool will represent a key technique in gathering quantitative player data. This tool will enable a more complete model of human play behaviour to be built because of the volume of data it captures and the power it gives the researcher to query that data effectively. Gathering player data can be difficult and any method that can do so without explicitly asking the player for feedback is beneficial in games design [10].

The simple setup for the experiment was as follows. Ten human players each played one game session of the FPS game Unreal Tournament 3 on the *Rising Sun* level for ten minutes against a single computer controlled opponent in a controlled environment. Data was extracted from each of these games using the *Digital Footprints mutator*. This mutator is a small program which modifies the game engine of unreal tournament and allows the *Digital Footprints* tool to analyse the data gathered after the game was complete. *Digital Footprints* itself is a separate application written in C# and run after the game has finished which processes the gathered data and generates diagrams and charts including heat maps. More details of the analysis as well as the results will be outlined in the following section.

3 Findings

The findings for this experiment focus on the area of navigation. These findings represent the distribution of time by the human players and their bot counterparts spent in each part of the level. Put simply, this is how much time the players spent in each area of the map. This is represented by *Digital Footprints* as a Heat Map.

Figure 3 is a detailed heat map of a human player's location data in the level.

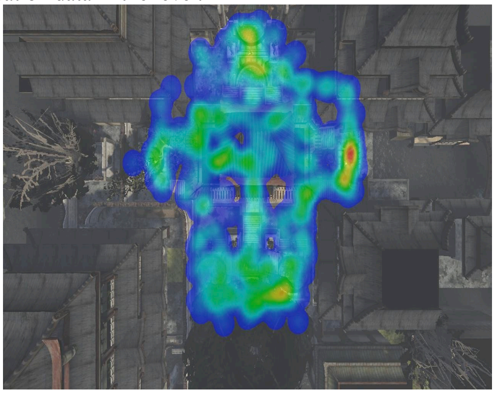

Figure 3. Heat map of human player navigation

This can be compared to a bot heatmap of location data as shown in figure 4.

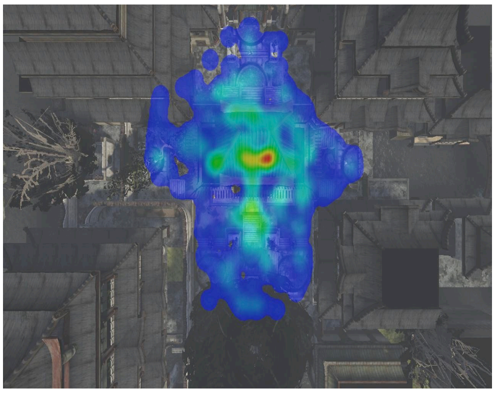

Figure 4. Heat map of bots navigation

Cursory examination of the two heatmaps shows obvious differences. This in itself provides little insight as variations between players would be expected regardless of whether they were human or bot controlled. Despite this, more careful examination of all of the heat maps shows that regardless of their opponent, all of the bot heat maps show significant similarities. The human heat maps meanwhile show more variation, but can similarly be logically grouped together based on appearance. It would be repetitious to print all heat maps in this paper, but further examples below in figure 3 and 4 show the continued similarities.

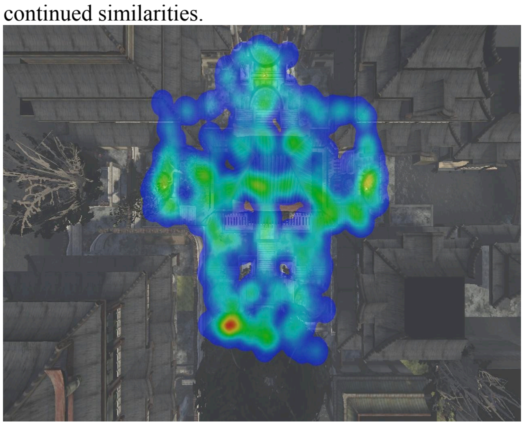

Figure 5. Additional heat map of human navigation

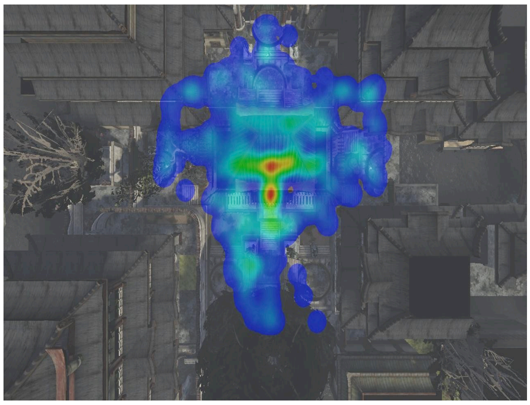

Figure 6. Additional heat map of bots navigation

Merely looking at the heatmaps provides useful information on bot and human play behaviour. A more robust method of differentiating and interpreting the data is necessary however. It is important to determine whether the differences are observable only to the authors of this paper. To eliminate any possible bias, impartial observers were asked to help.

To do this, ten people were asked to group the heatmaps based on their basic structure and appearance into two sets. Each individual would examine the ten heatmaps for human players and the ten for bots from the games that were played and split them into type one or type two. The people asked to help did not know anything about the heatmaps and most were not even games players.

Of the ten people asked to do this, nine of them were able to correctly group all of the heatmaps into the correct categories of bot and human. This is a significant and is provided here as evidence to support the observations made by the authors.

This method of determining whether bot and human heatmaps are noticeably different is quite primitive. Future work, discussed in more detail later, will consider an algorithm which could be used to automate this process.

It can be seen that from examination of the heat map generated from a game alone we could determine whether the data was for a human or bot player. This supports previous work which shows that human players can easily differentiate between human and bot opponents [3]. In this paper by Welsh, navigation was highlighted as one of the most important areas of differentiation between humans and bots with many players surveyed mentioning how disappointing the movements of the bots in the game were.

Looking at the heat maps in more detail, it can be seen that there are areas of the map that the bot never travels through. Additionally, the bot spends more time around the centre of the map and generally moves around less than human players.

4 Exposition and conclusion

This work represents an initial attempt to use the software tool *Digital Footprints* to determine if it can be used to discover meaningful data that can be used to improve bot behavior. From the data gathered we can see that there are noticeable differences between human and bot play behavior and these differences include the way that bots and human navigate through a level. This work focuses on only one area: navigation. Despite this it nonetheless provides clear evidence showing the large disparity between human and bot behavior.

To consider the usefulness of these findings we must consider how they could be used to improve bot behavior. One possibility is that at the simplest level, the bot paths used by the bots could be modified. These results show that the bots do not move through the level in the same way that human players do. By using the heatmaps for human players as a reference, we could adjust these bot paths.

Bots navigate through a level based upon a series of nodes set out by a level designer. This experiment has shown that these bot paths are not representative of human navigation. It is possible therefore those substantial improvements in bot believability could be achieved by using human generated heat maps to influence bot navigation. This could be done sim ply by adjusting the navigation points of the bots with the software and development tools included with the game. This could be performed offline as part of the game design process or even online as part of a learning algorithm in a more complex client-side bot as considered in other work by Spronk et al [11].

5. Further Work

This represents only the beginning of the functionality offered by *Digital Footprints* utilising only the simplest of the functions provided by the software. By examining only the navigation of the players we have already gathered useful information on human and bot player behavior. By expanding the data gathered to include weapon choice, kill and death locations and weapon trajectories it will be possible to more fully capture human play behavior and gain a more complete understanding of how to replicate this behavior in bots.

There are a number of different directions this work should be taken in the future. Firstly, this tool has shown that it is effective in capturing human player behavior. As has been argued, human play behavior is currently poorly understood and only by carefully studying that behavior can we attempt to capture it in bot play behaviour [3].

This paper has also shown a key difference between human and bot play behavior: navigation. In this instance the way that human and bot players move through the game environment is very different. This could be one key reason why bots are often perceived as poorer opponents than humans [7]. By examining heat maps generated by human players it should be possible to create bot paths which more closely correspond to human player's movements. This process could be strengthened further by automating it with an algorithm which would analyse heat maps and differentiate bot and human behaviour. A tool which differentiated between humans and bot could be a key tool in testing the performance of bot and a useful interface for tool for developers. Furthermore, by aggregating many human players' heat map data during the design stage of a level it should be possible to test and refine bot behavior. A useful experiment would be to try this and create bot paths based upon such heat maps. The result of this could be more convincing and believable bots.

Digital Footprints is a versatile and powerful tool. With creativity and adaptation it can be used in a number of ways in AI design, game design and testing. In this case it has been used to successfully demonstrate key differences in human and bot play behavior. In highlighting navigation as a problem area, it has also given an indication of where AI developers and programmers may look to improve the bots that they create in the future.

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